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RESEARCH ARTICLE

EDGE-BASED JUNCTION DETECTOR OPERATOR ON CIRCUMFERENTIAL ANCHORS FOR 3D RECONSTRUCTION

M. Shenbagam[1], V. Vivekanandhan[2]
Jayaram College of Engineering and Technology
Department of Computer Science and Engineering
[1] shen_jo@rediff.com, [2] vivek_7677@hotmail.com

Abstract - A junction is defined as a meeting point of two or more ridges in the gradient domain into which an image can be transformed through Gaussian derivative filters. To accelerate the detection process, two binary edge maps are produced; a thick-edge map is obtained by imposing a threshold on the gradient magnitude image, and another thin-edge map is obtained by calculating the local maxima. Circular masks are centered at putative junctions in the thick-edge map, and the so-called circumferential anchors or CA points are detected in the thin map. Radial lines are scanned to determine the presence of junctions. JUDOCA Introduce a new algorithm for measuring the detection accuracy and so-called junction coordinate systems. In proposed system the Location of the Edge will be detected accurately in 3D Reconstruction and reconnect the edges.

Index terms - MoravecCorner Detection Algorithm; SUSAN; JUDOCA

I. INTRODUCTION

1.1 FEATURE DETECTORS

Feature detection in images is a fundamental problem in computer vision. In many vision systems, detecting features can be used as a first step toward a more complicated stream of processes. Hence, the reliability of such a step can greatly affect the overall outcome of the vision system. During the past decades, many feature detectors were proposed. Those compete with each other in terms of localization accuracy, speed, and the information it provide. Different types of features are found useful for recognition (e.g., edges and corners). An edge can be defined as a gradual transition in the intensity level. On the other hand, a corner may not have a single universal definition. A corner can be defined as a point with low self-similarity or a location where variations of the intensity function in both directions are high. Alternatively, a corner may be defined as an image point where two or more edges meet. Different corner detectors are built on top of different definitions, which lead to different outcomes that vary not only in the number of corners detected but in the location accuracy and speed of the process. Sometimes, the term interest point may be used instead of a corner. However, if the interest point is a position that can be robustly detected an end of a line can be considered as an interest point as it may have local intensity maximum or minimum, or low self-similarity. Similarly, isolated points or curve points with local maximum may be detected as interest points. It is worth noting that most of the corner or interest-point detectors are concerned with detecting only the locations of those points. Most of the time, the criterion upon which the detection is based is neglected (e.g., local dissimilarity based on intensity variations).

1.2 JUNCTION DETECTORS

Junction detectors do the job of identifying both locations and the information used to make the identification. For example, if a corner is considered as the intersection of two edges, then a junction can be identified by its location and the orientations of the edges forming it. This results in richer information that can be important for recognition. It describes an operator that has the advantage of providing accurate junction localization and characterization. These feature characteristics can be exploited to make recognition more viewpoint invariant. The proposed operator has been successfully used in many applications e.g., wide baseline matching, 3-D reconstruction, camera parameter enhancing, indoor localization, and obstacle localization.

1.3 CORNER DETECTORS

Corner detection is an approach used within computer vision systems to extract certain kinds of features and infer the contents of an image. Corner detection is frequently used in motion detection, image registration, video tracking, image moseying, panorama stitching, 3D modeling and object recognition. Corner detection overlaps with the topic of interest point detection.

Figure 1.1 Example for Corner detector

1.3.1The MoravecCorner Detection Algorithm

This is one of the earliest corner detection algorithms and defines a corner to be a point with low self-similarity. The algorithm tests each pixel in the image to see if a corner is present, by considering how similar a patch centered on the pixel is to nearby, largely overlapping patches. The similarity is measured by taking the sum of squared differences (SSD) between the two patches. A lower number indicates more similarity. If the pixel is in a region of uniform intensity, then the nearby patches will look similar. If the pixel is on an edge, then nearby patches in a direction perpendicular to the edge will look quite different, but nearby patches in a direction parallel to the edge will result only in a small change. If the pixel is on a feature with variation in all directions, then none of the nearby patches will look similar. The corner strength is defined as the smallest SSD between the patch and its neighbors (horizontal, vertical and on the two diagonals). If this number is locally maximal, then a feature of interest is present. As pointed out by Moravec, one of the main problems with this operator is that it is not isotropic if an edge is present that is not in the direction of the neighbors, then it will not be detected as an interest point.

1.3.2 The Susan Corner Detector

SUSAN is an acronym standing for Smallest Univalve Segment Assimilating Nucleus for feature detection, SUSAN places a circular mask over the pixel to be tested (the nucleus). The region of the mask is M, and a pixel in this mask is represented by $\vec{m} \in M$ The nucleus is at . Every pixel is compared to the nucleus using the comparison function

$$c(\vec{m}) = e^{-\left(\frac{(I(\vec{m})-I(\vec{m}_0))}{t}\right)^6}$$

Where t determines the radius, and the power of the exponent has been determined empirically. This function has the appearance of a smoothed top-hat or rectangular function. The area of the SUSAN is given by

$$n(M) = \sum_{\vec{m} \in M} c(\vec{m})$$

If c is the rectangular function, then n is the number of pixels in the mask which are within t of the nucleus. The response of the SUSAN operator is given by

$$R(M) = \begin{cases} g - n(M) & \text{if } n(M) < g \\ 0 & \text{otherwise,} \end{cases}$$

Where g is named the `geometric threshold'. In other words the SUSAN operator only has a positive score if the area is small enough. The smallest SUSAN locally can be found using non-maximal suppression, and this is the complete SUSAN operator. The value determines how similar points have to be to the nucleus before it is considered to be part of the univalve segment. The value of g determines the minimum size of the univalve segment. If g is large enough, then this becomes an edge detector.
For corner detection, two further steps are used. Firstly, the centroid of the SUSAN is found. A proper corner will have the centroid far from the nucleus. The second step insists that all points on the line from the nucleus through the centroid out to the edge of the mask are in the SUSAN.

1.3.3 FAST corner detector

The first corner detection algorithm based on the AST is FAST (Features from Accelerated Segment Test). Although can in principle take any value, FAST uses only a value of 3 (corresponding to a circle of 16 pixels circumference), and tests show that the best results are achieved with n being 9. This value of n is the lowest one at which edges are not detected. The order in which pixels are tested is determined by the ID3 algorithm from a training set of images.

II. PROPOSED WORK

Methods for characterizing junctions have been proposed. However, their computational complexity does not generally allow them to be used for junction detection and localization. It would instead be applied on selected interest points having been previously detected by some efficient corner detector as in, which is based on the successive application of rotated wedge-averaging filters around a given key point. The approach described in detects junctions using a piecewise constant function that partitions a circular template into wedge-shaped regions. The junctions and contours of the model, replace the user interaction. Junctions will provide us an efficient mechanism to generate candidate matches, while contours will select the correct match based on a robust shape similarity evaluation. The detection and the characterization are achieved through energy minimization in order to find the best approximating junction model.

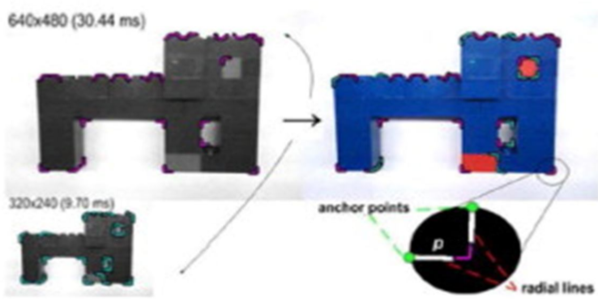


Figure 2.1 Junction Extraction

Junction extraction developed by JUDOCA. It combines the junctions of two image resolutions (left) to improve detection (right). The junction extraction procedure has also been enlarged for clarity. An image gradient is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images. At each image point, the gradient vector points in the direction of largest possible intensity increase, and the length of the gradient vector corresponds to the rate of change in that direction. Since the intensity function of a digital image is only known at discrete points, derivatives of this function cannot be defined unless it assume that there is an underlying continuous intensity function which has been sampled at the image points. With some additional assumptions, the derivative of the continuous intensity function can be computed as a function on the sampled intensity function, i.e., the digital image. It turns out that the derivatives at any particular point are functions of the intensity values at virtually all image points

2.1 ADVANTAGE

1. The JUDOCA algorithm detects the junctions in accurate manner when compared to other detectors. This detector solves many problems like wide baseline matching, 3D reconstruction, camera parameter enhancing, indoor and obstacle localization.
2. It overcome the existing disadvantage and provides the accurate locations of junctions.

III. ARCHITECTURE DIAGRAM

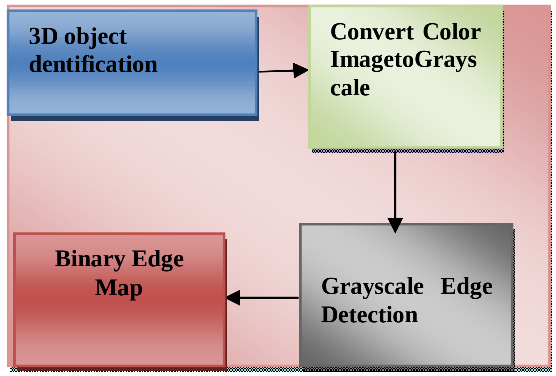


Figure 3.1 Identification of 3D Representation

3.2.1 JUDOCA PROCEDURE

Apply vertical and horizontal Gaussian derivative filters on image I.

1. Compute the gradient magnitude and create two binary images from it,
   a. The first one B, it is created by imposing a threshold tB ,on the gradient image.
   b. The second one, B+, contains the points of B that are local maxima in the Direction of Gradient.
2. For each point p in B, consider a circle of radius ½ centered on this point and obtain the list of candidate points qi in B+ that lie on the circumference of this circle

These so-called circumferential anchor (CA) points are the extremities of potential radial lines for the putative junction.

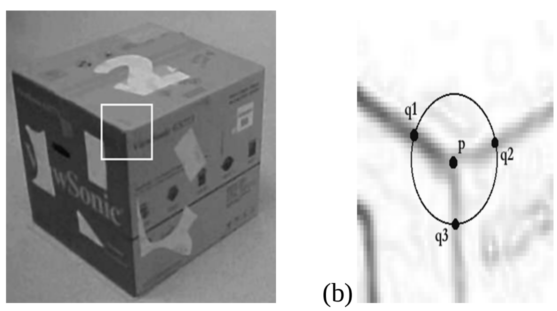
(a) (b)


Figure 3.2.1 (a) one corner of a box that produces a Y-junction. 3.2.1(b) The junction at p with three CA

3. For each CA point qi in the list, consider the set of all points located at a distance less than one pixel to the segment that joins the current CA point to the central point p. This set is used to determine if the corresponding putative junction radial line will be accepted (considering the points in B) and if yes, what the strength of this junction line would be (considering the points in B+), that is,
   a. To be accepted as a junction line, a continuous path of B points joining the CA point and the central point p must exist. If not, then reject this radial line and repeat the scanning operation with the next CA point.
   b. The strength, SJ (< p; qi >), of this junction radial line is defined as the sum of the squared distances from the B+ points in the currently considered set to the < p; qi > line segment. This strength is normalized by the length of this segment.
5. If the strength of this junction radial line is smaller than a predetermined threshold, sJ , then reject this radial line. Otherwise, < p; qi > becomes one of the branch of the putative junction at p.
6. If the number of branches found at p is less than 2, then there is no junction at this location. Otherwise, record the orientation of the accepted junction radial lines and set the strength, SJ (p), of this junction as being the minimum across all radial line strengths,

SJ (p) = mini Sj(< p; qi >) (1)

In the particular case of 2-junction, an extra step must be undertake in order to ensure that this junction is not, in fact, a simple line. This can be verified by looking at the angle between the two radial lines. If this one is close to 180±, then the junction should be rejected. In practice, a threshold is set on the maximal and minimal acceptable angle for 2- junctions. Additionally, the strength of the junction can be used to perform a non-maxima suppression post processing phase to eliminate clusters of junction that could arise, especially if a permissive threshold is used in Step 5. Different definitions for the junction strength could have been adopted. However, the one given in Step 6 is based on an assertion stating that a junction is as weak as its weakest branch. This definition also implies that a weak N-junctions can be transformed into a stronger (N ¡ 1)-junction.

IV. CONCLUSION AND FUTURE WORK

The new technique JUDOCA is used to detect junctions in the image and their locations. From the literature survey the junctions are identified but the locations are not identified. It has the limitations that, it does not support for reconnecting the edges, and does not support for the color images. In the proposed system a new method is used to measure the location accuracy. Based on the edge detection survey the expected outcome would be able to support efficient evaluation of 3d-reconstruction. In future the remaining functions are to be implemented and additional technique can be used to detect the junctions in the image for enhancement of locating the objects.

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